Eur J Ageing (2010) 7:135–146
DOI 10.1007/s10433-010-0161-5

ORIGINAL INVESTIGATION

Five views of a secret: does cognition change during middle adulthood?

Daniel Zimprich · Anna Mascherek

Published online: 25 August 2010

Abstract This study examined five aspects of change (or stability) in cognitive abilities in middle adulthood across a 12-year period. Data come from the Interdisciplinary Study on Adult Development. The sample consisted of $N = 346$ adults (43.8 years on average, 48.6% female). In total, 11 cognitive tests were administered to assess fluid and crystallized intelligence, memory, and processing speed. In a first series of analyses, strong measurement invariance was established. Subsequently, structural stability, differential stability, stability of divergence, absolute stability, and the generality of changes were examined. Factor covariances were shown to be equal across time, implying structural stability. Stability coefficients were around .90 for fluid and crystallized intelligence, and speed, indicating high, yet not perfect differential stability. The coefficient for memory was .58. Only in processing speed the variance increased across time, indicating heterogeneity in interindividual development. Significant mean-level changes emerged, with an increase in crystallized intelligence and decline in the other three abilities. A number of correlations among changes in cognitive abilities were significant, implying that cognitive changes in middle adulthood share up to 50 percent of variance.

Keywords Cognitive change · Middle adulthood · Measurement invariance · Intraindividual change · Interindividual change

Communicated by M. Martin, S. L. Willis, C. Röcke, D. J. H. Deeg.

D. Zimprich (✉) · A. Mascherek
Department of Gerontopsychology, Institute of Psychology, University of Zurich, Binzmühlestrasse, 14/Box 24, 8050 Zürich, Switzerland
e-mail: d.zimprich@psychologie.uzh.ch

Does cognitive performance change during middle adulthood? For many, middle adulthood represents a phase of stability, during which hardly any developmental changes are observed. Although some authors (e.g., Schaie 1994; Hertzog and Schaie 1986, 1988) have addressed cognitive development in middle-aged persons, altogether, there are only few studies concerning the topic in this age group. Thus, the question of whether or not cognition changes between the 40s and 60s still comes, at least in part, in form of a secret. This is also the case because there are different perspectives on cognitive change (e.g., Schaie 1974; Hess 2005). In the present study, we aim to shed some light on this secret by examining 12-year changes of cognition in a sample of middle-aged adults.

Although developmental and cognitive aging researchers tend to think of single individuals and the way their cognitive performance changes across time, what they usually examine are the data of groups or samples of persons. In such sample data, several statistical parameters can be used to describe the distribution of cognitive performance differences and their associations across time. Typical parameters are means, variances, and covariances, all of which may be subject to change over time. The question of whether cognition changes in middle adulthood or whether it remains stable can, thus, be answered in several ways, depending on what type of change (or stability) one focuses on. As we will demonstrate in this paper, there are (at least) five types of change (or stability) that can be examined using longitudinal sample data. Thus, there are "five views of a secret," namely, of whether cognition changes during middle adulthood.

Interestingly, the parameter least informative with respect to the change of single individuals is the one most often studied, namely, the mean. From the fact that the mean of sample data does not change, one could conclude that no single individual changes if in addition, it is assumed that the mean is representative for all individuals or, which is the same, that there are no interindividual differences in intraindividual change—an assumption which can hardly ever be true. In the following, we expand the perspective of mean changes (or absolute change) by four other types of change (or stability), namely, structural change, differential change, change in divergence, and general versus specific change (Allemand et al. 2007).

Structural change (*or stability*) refers to the constancy of covariances among a set of variables across time or in different age groups. In other words, structural change addresses the issue of changing associations among psychological constructs over time. In cognitive aging research, the question mainly addressed in investigating structural stability refers to differentiation or dedifferentiation, that is, a change in structure. Empirically, structural stability is assessed by comparing the covariation pattern among variables. In order to exclude changes or differences in covariances due to measurement error, factor analysis techniques are commonly used, and structural stability is then examined on the latent level. However, this requires that constructs are measured in the same way on different measurement occasions or in different age groups. In order to guarantee this, several degrees of measurement invariance (MI) can be examined (see Meredith 1993). *Configural invariance* entails that the number of factors and according salient and non-salient loadings are equal across age groups or over time, which ensures that the dimensionality of the measured construct is equivalent. For *weak MI* to hold, factor loadings must be equal. If so, factor variances and covariances can be compared. If in addition, the intercepts of the manifest indicators are equal, *strong MI* is given, which allows comparing factor means. Eventually, if residual variances are also equal, *strict MI* holds, implying that all interindividual differences in observed variables stem from the underlying factors (cf. Bollen 1989; Meredith and Horn 2001).

Empirical research on structural stability in middle adulthood is sparse at present. A special case of structural change is the question of differentiation or dedifferentiation of cognitive abilities with advancing age (e.g., Ghisletta and Lindenberger 2003; Zelinsky and Lewis 2003). Differentiation denotes a decrease of covariances across time or in older age groups, while dedifferentiation refers to an increase of covariances. Some cross-sectional studies have provided empirical support for cognitive dedifferentiation in older adults (Babcock et al. 1997; Baltes et al. 1980; Hertzog and Bleckley 2001). In other cross-sectional studies, contrary findings, i.e., a differentiation of cognitive abilities with age, have been reported (Cunningham et al. 1975; Schmidt and Botwinick 1989; Tomer and Cunningham 1993, Tucker-Drob and Salthouse 2008), or results supported neither differentiation nor dedifferentiation (Bickley et al. 1995; Cunningham and Birren 1980; Juan-Espinosa et al. 2000, 2002; Park et al. 2002; Sims et al. 2009). Thus, the question of dedifferentiation appears to represent an unresolved issue in cross-sectional data. To our knowledge, only few longitudinal studies examined cognitive dedifferentiation in old age. Anstey et al. (2003) did not find consistent patterns of dedifferentiation. In contrast, in a sample of 377 individuals aged 79 years and older, Ghisletta and de Ribaupierre (2005) did find corroborative results for dedifferentiation of cognitive abilities in late life (see also de Frias et al. 2007). Hence, longitudinal research on cognitive dedifferentiation is also inconclusive. Notably, structural stability has hardly ever been investigated in samples of middle-aged individuals. In what follows, we aim at examining this issue longitudinally.

Differential change (*or stability*) refers to the retention of an individual's relative placement within a group across time. Consistency of interindividual differences may only be assessed longitudinally because it requires at least two measurement occasions. Conceptually, differential change implies that some individuals change to a larger (or smaller) amount than others across time. It describes how change in a specific variable affects the rank order of individuals. Different people may change to a different degree across time. These differences cannot be depicted in mean-level analyses. Hence, even with perfect mean-level stability or stability of divergence (see below), the rank order of the individuals may change across time. Traditionally, correlations across time have been computed for manifest variables of cognitive abilities. Although random errors should cancel out across repeated assessments, there might be other systematic influences, e.g., method effects or unreliability, which may qualify the comparison of observed scores across time. Again, a possible strategy to diminish such unwanted influences might be to examine differential change (or stability) on the latent level (cf. Martin and Zimprich 2005).

One problem with differential change is that no mandatory guidelines exist as when to say stability is low enough for being indicative of substantial change. Thus, it remains an open question whether correlations of .90 might be interpreted as stability with only negligible change or as change because of the deviation from perfect stability (i.e., 1.0). In our investigation, we thus tested whether differential stabilities were significantly smaller than one. To our knowledge, differential change (or stability) in middle adulthood has only rarely been examined to date. Hertzog and Schaie (1986, 1988) examined general intelligence over a 14-year period with measurement intervals of 7 years in three age groups (young: 25–32, middle: 39–46, old: 53–67 years of age at first measurement). In all three age groups, factor correlations of general intelligence were as high as $r = .95$ between times 1 and 2 and $r = .92$ between times 1 and 3, thus indicating stable, yet not perfect, interindividual differences. Similarly, Larsen et al. (2008) found differential stabilities of $r = .82$ and $r = .79$, in verbal and arithmetic subtests, respectively, in a sample of middle-aged adults across 18 years. Our expectation thus was to find relatively strong, albeit not perfect, differential stability in middle adulthood across 12 years.

Change (*or stability*) *of divergence* refers to the fact that the amount of interindividual differences in a cognitive ability might change over time or be different in different age groups. Do individuals become more or less similar over time? This implies that across time the variances of cognitive measures may decrease or increase (Preece 1982). Change in variances implies interindividual differences in the amount of change. Conceptually, increasing variances indicate increasing heterogeneity; decreasing variances, in turn, indicate growing homogeneity with respect to interindividual differences in cognitive abilities. Change of divergence conceptually refers to the so-called "fanspread-phenomenon," which means that the pattern of trajectories resembles a converging or diverging fan-spread (Preece 1982). To date, there are only few results dealing with change or stability of divergence of cognitive abilities in middle age. Martin and Zimprich (2005) showed that the variance in processing speed significantly changed across a 4-year period in middle-aged adults, whereas the variance in memory did not. From that one might conclude that—irrespective of differential stability or change—there are interindividual differences in the amount of change in processing speed. For the present investigation, we thus expected change of divergence at least in processing speed, but maybe also in other cognitive abilities taking into account the longitudinal time span of 12 years.

Absolute change (*or stability*) refers to change in the mean of a cognitive ability over time or across age groups. Conceptually, absolute change reflects the amount of average change that is present in a psychological construct or cognitive ability. With absolute change one can describe trends within a given sample or population but cannot describe how a given variable changes for a single individual. Traditionally, sample means of cognitive abilities have been compared in order to test for absolute change (e.g., Schaie 1996). Using latent growth models, Finkel et al. (2003) found that, across a 6-year period, the longitudinal rate of decline in a sample of 590 adults aged 44–88 years accelerated from middle to later adulthood for some cognitive abilities. A single-slope estimate provided sufficient description of the data for half of the cognitive measures, meaning that the rate of decline in these abilities did not differ by age groups. Thus, accelerating decline at the transition from middle to late adulthood seems to be evident for some, but not all, cognitive abilities. Similarly, Finkel et al. (1998) reported that middle-aged adults (55 years) performed significantly better than old adults (83 years) in all tests of a battery of 14 cognitive abilities. The largest age differences in mean performance were found for measures of perceptual speed. Soederberg Miller and Lachman (2000) investigated whether midlife is a time of peak performance in the area of cognitive functioning. Comparing the average performance of 84 young adults (25–39 years), 108 middle-aged adults (40–59 years), and 67 older adults (60–75 years) in speed, reasoning, short-term memory, and vocabulary, they found that middle-aged adults showed little or no cognitive decline in cognitive performance and even outperformed the young on vocabulary. Relative to older adults, middle-aged adults scored higher on all tasks except for vocabulary, where no differences emerged. Larsen et al. (2008) reported a significant increase in verbal score but no change in arithmetic scores across 18 years in a sample of more than 4,000 males for two measurement occasions (ages 19 and 38). This underlines the possible gain in vocabulary in middle adulthood.

Like with the other types of change, there are advantages in assessing absolute change (or stability) on the latent level by comparing factor means across time or age groups. Horn and McArdle (1992), for example, after having established strong MI, found that compared to young (16–22 years) and old (67–72 years) adults the average verbal cognitive component in the WAIS-R was highest in both middle-aged adults groups (30–40, 50–60 years), whereas the average performance cognitive component was highest in the younger age group and the younger of the two middle-aged-cohorts. Specifically, the effect size for the verbal cognitive component was about Cohen's $d = .40$, indicating a small to medium performance difference favoring middle-aged adults (cf. Cohen 1987). Taken together, in our sample of middle-aged adults followed for 12 years, we thus expected a longitudinal performance increase in measures of crystallized intelligence, but a longitudinal decline in fluid intelligence, memory, and processing speed.

Specific versus general change (*or stability*) refers to the question of whether different cognitive abilities change together over time, that is, whether changes are correlated across different cognitive abilities. If so, cognitive change would be relatively general. Conceptually, general change describes if one mechanism operates simultaneously on different cognitive domains. If this is the case, then intraindividual changes should be rather general across different cognitive aspects. Empirically, specific versus general stability can be assessed by correlating interindividual differences in intraindividual change in different cognitive abilities. General change should lead to substantial correlations among the different cognitive factors. In order to assess change precisely, latent change models are commonly used. The level of the latent construct and the change of this construct are then estimated. These models enable to test whether change in one variable predicts change in another variable (Hertzog and Nesselroade 2003). Hultsch et al. (1998), using data from the Victoria Longitudinal Study, specified a common factor model of cognitive change for a number of measures of intellectual abilities. They found that there was some commonality of changes across different cognitive abilities. Zimprich (2002) modeled a common change factor of cognitive abilities using data from the Bonn Longitudinal Study on Aging and the older cohort from the Interdisciplinary Longitudinal Study on Adult Development. Findings indicated some shared variance among cognitive changes. More recently, Christensen et al. (2004) fitted a common factor of change in cognitive abilities to data from the Canberra Longitudinal Study. Zimprich and Martin (2009), using a multilevel factor analysis approach, reported that in old adults on the level of factors longitudinal changes were as strongly correlated as cross-sectional age differences. Note that these studies have focused on old age, where more pronounced changes are to be expected than in middle adulthood. Thus, we expected to see some correlated change in middle-aged adults, but that, similar to older persons, correlations would be weaker compared to cross-sectional correlations.

In order to summarize, in this study, we concentrate on five different aspects of change (or stability) of cognitive abilities in middle adulthood. Structural change, differential change, absolute change, change of divergence, and specific versus general change in 11 cognitive tasks representing four cognitive abilities are examined in a middle-aged group across a 12-year period. Although the cited empirical evidence mainly relies on older adults, leaning on these results we expected to find both stability and change of cognitive abilities in middle adulthood.

Method

Sample

Data come from the Interdisciplinary Study on Adult Development (ILSE, Martin et al. 2000) an ongoing interdisciplinary longitudinal study on the psychological, physical, and social antecedents and consequences of aging in Germany. This study included persons who belong to the younger of the two cohorts in ILSE and who had complete data records for the variables of interest at the first and the third measurement occasions in 1994 and 2006, resulting in a sample size of $N = 346$. On average, participants were 43.8 years old at T1 in 1994 (SD 0.9 years). About 48.6% of the sample were female. The reason for discarding the data from the second measurement occasion in 1998 was that only a reduced battery of cognitive tests was administered in the younger cohort. Compared to those 203 subjects who dropped out before T3 (of whom 57 left the study before T2), those who stayed in the study showed a higher performance at T1 in almost all cognitive tasks. Effect sizes were small, however, ranging from 3% of explained variance in the picture completion test to 0% in the delayed Picture Recall test (for a description of tests, see below). On average, the effect size was 1.7%. Hence, although the sample appears to have become slightly more selective between T1 and T3, one might still consider it as reasonably representative.

Measures

Processing speed

Speed was assessed using two different instruments: the number-connecting test designed for older adults and the digit symbol substitution test.

Number connecting The number-connecting test (Oswald and Roth 1987) is a timed paper–pencil test requiring participants to connect successive numbers. Participants had to finish five working sheets, the first three of which served as practice trials. The dependent variables were the times (in seconds) to complete the last two sheets. The results from the number-connecting test were reversed so that high values indicate better performance. Since the results of the number-connecting test departed significantly from normality, they were Box–Cox-transformed (cf. Box and Cox 1964) using $\lambda = -0.8$ for both trials at both measurement occasions.

Digit symbol substitution This task was taken from the German version of the WAIS-R (Tewes 1991). The participant is requested to match symbols with digits according to a given coding table. The dependent variable is the number of correctly copied symbols on a working sheet within 90 s (possible range 0–67 points).

Fluid intelligence

Fluid intelligence was assessed using three different manifest indicators, namely, Spatial ability, block design, and picture completion.

Spatial ability This task required participants to count the number of surfaces (including hidden ones) in 40 different three-dimensional images of geometrical figures taken from the LPS (Horn 1983). In total, participants were given 3 min to work on the task. Every correct answer was scored with one point. Correct responses were summed in order to form a total score of spatial ability (possible range: 0–40).

Block design This task, which was taken from the German version of the WAIS-R (Tewes 1991), required participants to reproduce abstract patterns using nine colored blocks. The nine item scores were added to form a total score of block design (possible range: 0–51).

Picture completion This task, which stemmed from the German WAIS-R (Tewes 1991), required participants to mention details that were missing on pictures of simple objects (e.g., a car with a missing wheel). In total, there were 17 pictures. Every correct response was scored with one point. Correct responses were added to form a total score of picture completion (possible range: 0–17).

Crystallized intelligence

Crystallized intelligence was measured using three different manifest indicators, namely, picture completion (see above), information, and similarities. As McArdle and Prescott (1992) have shown, picture completion can be conceptualized as being a marker of both fluid intelligence—participants have to reason which logically necessary part of an object is missing—and crystallized intelligence, because in order to recognize objects as familiar or common objects, knowledge is required (cf. Horn 1985).

Information This task, which was taken from the German WAIS-R (Tewes 1991), required participants to answer a total of 24 questions from different knowledge domains (e.g., what is an ode?). Every correct response was scored with one point. All correct responses were summed up to form a total score of information (possible range: 0–24).

Similarities For this task, which stemmed from the German WAIS-R (Tewes 1991), participants were asked to name what two concepts had in common (e.g., zoo—library). In total, there were 16 pairs of concepts. Depending on the quality of the response, correct solutions were scored with one or two points. Correct answers were added to form a total score of similarities (possible range: 0–32).

Memory

Memory was measured using a picture recall task, a delayed picture recall task, and a word recall task from a German gerontological test battery (Nuremberg Inventory of Old Age; Oswald and Fleischmann 1995).

Picture recall immediate For this task, seven pictures of objects were presented to the participants for 3 s each. After the presentation of all pictures, participants were immediately asked to recall as many objects as possible. Scored was the number of correctly recalled objects (possible range: 0–7 points).

Picture recall delayed The delayed picture recall task demanded recall of the same seven objects after a 30 min interval. Scored was the number of correctly recalled objects (possible range: 0–7 points).

Word list recall For the word list recall task, 12 words were read aloud to the participants in intervals of 2 s. Immediately after presentation, participants were asked to repeat as many of the words as they could remember. The number of correctly recalled words was scored (possible range: 0–12 points).

Statistical modeling

In order to investigate our research questions we utilized multiple-groups confirmatory factor analyses by means of structural equation modeling. We assessed MI over time and then performed direct statistical comparisons of the similarities and differences in the factor means, variances, and covariances among the constructs. In order to model the different types of change on the latent level, we started by investigating the amount of MI. After having established strong MI, we tested for structural stability by constraining the covariances among latent variables (processing speed, fluid intelligence, crystallized intelligence, and memory) to be equal at T1 and T2. Next, differential stability was examined by constraining across-time correlations of the latent variables between T1 and T2 to be equal to one. Subsequently, stability of divergence was investigated by constraining variances of the latent variables to be equal at T1 and T2. Next, absolute stability was examined by constraining the factor means of each latent variable to be equal at T1 and T2. Note that in these model comparisons, the amount of misfit was tested for statistical significance by calculating χ^2-difference test. Eventually, the generality of 12-year intraindividual changes in cognition was investigated by correlating the changes between T1 and T2 among the latent variables. Models were parameterized as described in more detail in Allemand et al. (2007) and Zimprich et al. (2006). Specifically, as recommended by Meredith and Horn (2001), factors were scaled in a way that all factor loadings were estimated instead of using a marker variable. In order to keep factors identified, factor means were set to zero and factors variances were constrained to be one. Depending on the model tested, these constraints were relaxed gradually (see the "Results" section).

All analyses were conducted using Mx (Neale et al. 2003). The absolute goodness-of-fit of models was evaluated using the χ^2-test and two additional criteria, the Comparative Fit Index (CFI) and the Root Mean Square

Error of Approximation (RMSEA). Values of the CFI above .90 are considered to be adequate, whereas for the RMSEA values less than .08 indicate an acceptable model fit (Browne and Cudeck 1993). In comparing the relative fit of nested models, we used the χ^2-difference test. We complemented the χ^2-difference by calculating 90% RMSEA confidence intervals for the models estimated (MacCallum et al. 1996).

Results

Table 1 contains descriptive statistics and intercorrelations of the 22 manifest indicator variables. As can be seen from Table 1, the stabilities especially for the indicators of memory were low, i.e., smaller than .71, which implies that the T1 and T3 measures shared less than 50% of variance. Also, the standard deviations of most manifest variables tend to increase over time, whereas means tend to decrease—apart from information, where average performance increased.

Measurement invariance

Structural equation modeling started with the configural invariance model of four correlated factors fluid intelligence, crystallized intelligence, memory, and processing speed, where at both measurement occasions each manifest variable served as an indicator of the factor it was designated to measure. In addition, the residuals of the manifest variables were allowed to covary over time to reflect the assumption that specific parts of these measures might be associated across time.[1] As can be seen from Table 2, the configural invariance model achieved an acceptable fit according to both the CFI and the RMSEA, although the chi-square-test indicated significant departures of the model from the data—which is also owed to the high power of this test in conjunction with many degrees of freedom. As a consequence, we considered the configural invariance model as adequately describing the data.

Subsequently, weak measurement across time was imposed by requiring the factor loadings to be equal at both T1 and T3 (Model Weak MI). As Table 2 shows, doing so did not significantly reduce model fit, implying that weak measurement holds. Thus, at both measurement occasions the scaling of the latent variables was equal, which allows variance and covariance comparisons of the factors across time. For all four factors, variances at T3 were somewhat larger than at T1, indicating that interindividual differences tended to increase from 1994 to 2006. A more stringent test of factor variance differences was conducted in conjunction with the investigation of stability of divergence (see below).

In the next model (Model Strong MI), intercepts of the manifest indicators were constrained to be equal across time, thus imposing strong MI. According to Table 2, the fit of this model was not statistically inferior to that of the previous one, from which one might conclude that strong MI holds across T1 and T3. Consequently, factor mean differences can be calculated across time, because all mean differences of the manifest indicators are due to differences in latent variable means in the strong invariance model. It turned out that for the factor of crystallized intelligence performance did, on average, increase across time, while for the other three factors fluid intelligence, memory, and processing speed there was a performance decline during the 12 years of middle adulthood. Factor mean differences were examined in more detail relating to absolute stability (see below).

Finally, strict MI was imposed by requiring residual variances of the 11 manifest indicator variables to be equal at T1 and T3 (Model Strict MI). As Table 2 shows, model fit decreased significantly compared to the previous model. Hence, it appeared as if at least some of the residual variances were different at the two measurement occasions. However, according to both the CFI and, especially, the RMSEA, these differences did not seem to be very pronounced. Notwithstanding, we concluded that strict measurement did not hold, which implied that not all differences in the variances of the manifest indicator variables were due to differences in factor variances. Note that for examining the five different types of change, as reported below, strict MI does not represent a prerequisite. It is sufficient to establish strong MI, which, according to Model Strong MI, held in the ILSE data.

Structural stability

In order to test for structural stability, i.e., the equality of covariation patterns of the latent variables at T1 and T3, factor covariances were constrained to be equal at both measurement occasions (Model Structural Stability). As can be seen from Table 2, doing so did not lead to a statistically significant decrement in model fit compared to the strong MI model. Hence, one might conclude that covariances among fluid intelligence, crystallized intelligence, memory, and processing speed were equal in 1994 and

[1] An anonymous reviewer noted that correlated residuals were not common practice. However, in conjunction with longitudinal data, the assumption of correlated residuals appears reasonable according to the factor-analytic model, where an observed score in a manifest variable is composed of a common factor score (e.g., fluid intelligence), a specific factor score, and measurement error (cf. Meredith and Horn, 2001). The specific factor might, for example, contain effects specific to the stimulus material or specific to the task. These specific parts may be associated over time.

Table 1 Descriptive statistics and correlations of the manifest variables

	Mean	SD	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.
1. Information T1	16.5	4.00																					
2. Similarities T1	26.3	4.69	.59																				
3. Picture completion T1	13.2	2.77	.49	.45																			
4. Spatial ability T1	25.0	6.45	.49	.43	.50																		
5. Block design T1	31.7	8.46	.41	.40	.39	.55																	
6. Number connecting 1 T1	12.4	2.59	.24	.23	.23	.37	.40																
7. Number connecting 2 T1	13.0	2.31	.25	.25	.25	.37	.43	.71															
8. Digit symbol subst. T1	54.3	9.44	.27	.33	.25	.31	.35	.49	.51														
9. Word list recall T1	6.41	1.50	.21	.31	.22	.17	.08	.11	.15	.24													
10. Picture recall imm. T1	5.87	0.90	.09	.19	.14	.09	.09	.15	.09	.24	.30												
11. Picture recall delayed T1	4.66	1.14	.05	.16	.10	.05	.11	.17	.10	.20	.24	.48											
12. Information T3	17.5	4.06	.84	.52	.43	.46	.32	.21	.20	.22	.18	.04	.03										
13. Similarities T3	26.3	4.57	.57	.69	.31	.35	.35	.28	.27	.34	.23	.16	.05	.57									
14. Picture completion T3	13.4	2.88	.47	.34	.46	.37	.35	.30	.27	.26	.16	.14	.08	.49	.41								
15. Spatial ability T3	24.9	6.30	.51	.42	.43	.80	.55	.37	.37	.28	.16	.12	.13	.49	.39	.42							
16. Block design T3	30.0	8.76	.39	.35	.37	.56	.78	.38	.41	.36	.10	.10	.07	.37	.37	.40	.58						
17. Number connecting 1 T3	11.8	2.73	.22	.23	.23	.29	.36	.61	.51	.52	.15	.19	.20	.20	.26	.21	.35	.38					
18. Number connecting 2 T3	12.3	2.51	.21	.29	.23	.36	.37	.61	.60	.52	.18	.20	.18	.19	.27	.26	.38	.41	.76				
19. Digit symbol subst. T3	52.1	10.4	.25	.31	.19	.28	.35	.49	.48	.81	.21	.21	.21	.22	.35	.23	.30	.37	.61	.61			
20. Word list recall T3	6.51	1.43	.26	.27	.18	.18	.14	.23	.20	.30	.24	.25	.20	.25	.32	.28	.23	.16	.33	.31	.40		
21. Picture recall imm. T3	5.73	0.90	.05	.19	.12	.04	.16	.19	.15	.21	.19	.24	.30	.04	.14	.15	.10	.14	.26	.26	.27	.24	
22. Picture recall delayed T3	4.24	1.40	−.02	.05	.08	.03	.06	.18	.14	.17	.14	.23	.47	−.01	.05	.16	.09	.11	.23	.20	.27	.27	.52

Note: *SD* standard deviation, *T1* first measurement occasion (1994), *Subst.* substitution, *Imm.* immediate, *T3* third measurement occasion (2006). $N = 346$

2006. Note that the structural stability model represents an overall, simultaneous test of the equality of all six factor covariances at T1 and T3. Individual covariances did show differences over time, notably the covariance between memory and processing speed, which increased considerably across time (T1: 0.343, T3: 0.657).[2] A model where the equality constraint of the memory—speed covariance was relaxed, achieved a significantly better fit than the Model Structural Stability ($\chi^2 = 341.6$, df = 190, $\Delta\chi^2 = 9.3$, df = 1, $p < .01$). Thus, it appears as if the covariance between memory and processing speed is larger at T3 than at T1. One could consider this as being indicative of dedifferentiation between memory and speed—albeit one should be cautious in interpreting this possibly spurious result, because the overall test did not show a significant difference.

Differential stability

In order to assess differential stability, the across-time factor correlations were estimated as based on Model Strong MI. Factor stabilities were .94 (fluid intelligence), .93 (crystallized intelligence), .58 (memory), and .91 (processing speed). Thus, with the exception of memory, differential stabilities were relatively high, although not perfect. This implies that the rank order of persons did not change very much in fluid intelligence, crystallized intelligence, and processing speed. By contrast, it appears as if memory performance was less stable with regard to interindividual differences across time. In an attempt to more rigorously test whether differential stabilities were perfect, i.e., equal to one, in the Model Differential Stability 1 (Table 2) across-time correlations of the factors were constrained to one. As Table 2 shows, the model of perfect stability represented a significant loss in fit compared to the strong invariance model, at least implying that not all of the differential stabilities were perfect. If only the stabilities of fluid intelligence, crystallized intelligence, and processing speed were constrained to be equal (Model Differential Stability 2), model fit increased again (see Table 2), but still was significantly inferior to that of the model of strong invariance. Hence, we concluded that differential stabilities were less than perfect, i.e., different from one. From this one might also conclude that there was differential development in cognition between 1994 and 2006, mostly so in memory.

[2] In a correlational metric, the difference is smaller, namely, $r = .34$ versus $r = .46$. Still, this implies that the amount of shared variance between memory and processing speed increased from 12 to 21%.

Table 2 Sequence of estimated models

Model	χ^2	df	$\Delta\chi^2$	Δdf	CFI	RMSEA	RMSEA 90% CI
Configural invariance	317.9*	170			0.964	0.050	0.042–0.059
Weak MI	321.7*	178	3.8*[a]	8	0.965	0.048	0.040–0.057
Strong MI	337.1*	185	15.4*[a]	7	0.963	0.049	0.040–0.057
Strict MI	366.0*	196	28.9*[a]	11	0.958	0.050	0.042–0.058
Structural stability	350.9*	191	13.8[a]*	6[a]	0.961	0.049	0.041–0.057
Differential stability 1	420.9*	189	83.8*[a]	4[a]	0.943	0.060	0.052–0.067
Differential stability 2	373.5*	188	36.4*[a]	3[a]	0.955	0.053	0.045–0.061
Stability of divergence 1	360.2*	189	23.1*[a]	4[a]	0.958	0.051	0.043–0.059
Stability of divergence 2	339.7*	188	2.6[a]*	3[a]	0.963	0.048	0.040–0.056
Absolute stability	474.4*	189	137.3*[a]	4[a]	0.930	0.066	0.059–0.074

Note: *df* degrees of freedom, *CFI* Comparative Fit Index, *RMSEA* root mean square error of approximation, *CI* confidence interval, *MI* measurement invariance, *differential stability 1* model of perfect across-time stability (i.e., differential stability = 1) on the latent level. *Differential stability 2* model of perfect across-time stability for fluid intelligence, crystallized intelligence, and processing speed. $N = 346$

* $p < .01$

[a] Represents the difference to Model Strong MI

Stability of divergence

In a first model (Model Stability of Divergence 1), factor variances of fluid intelligence, crystallized intelligence, memory, and processing speed were constrained to be equal over time, thus imposing equally pronounced interindividual differences at T1 and T3. As Table 2 shows, such a model did not achieve an adequate fit compared to the strong MI model. Hence, at least one factor variance was significantly changing across time. Upon inspection, the variance of processing speed increased considerably (T1: 1.00, T3: 1.47). In a subsequent model (Model Stability of Divergence 2), only the factor variances of fluid intelligence, crystallized intelligence, and memory were constrained to be constant over time. According to Table 2, the fit of this second stability of divergence model did not differ significantly from that of the strong MI model. From this, we concluded that the amount of interindividual differences increased in processing speed over time, while for fluid intelligence, crystallized intelligence, and memory it remained constant across the two measurement occasions.

Absolute stability

As an overall test of factor mean differences between T1 and T3, factor means were constrained to be equal to zero at both measurement occasions (Model Absolute Stability). Table 2 reveals that such a model did not achieve an adequate model fit compared to the strong MI model. Hence, at least one factor mean difference was different from zero. When factor means were estimated freely as based on the model of strong MI, they were −0.145 (fluid intelligence), 0.296 (crystallized intelligence), −0.362 (memory), and −0.347 (processing speed), all of which were statistically significant ($p < .01$). Since factors are scaled differently, a direct comparison of factor mean differences is not warranted. If transformed to effect sizes (Cohen's d for repeated measures), factor mean differences become $d = -0.41$ (fluid intelligence), $d = 0.79$ (crystallized intelligence), $d = -0.37$ (memory), and $d = -0.74$ (processing speed). Thus, factor mean differences were in the medium effect size range for fluid intelligence and memory. By contrast, there were strong effects for both crystallized intelligence and processing speed, albeit in different directions, that is, an increase versus a decrease in performance across 12 years. Figure 1 depicts the factor mean change effect sizes.

Generality of change (correlated change)

In order to assess the generality of intraindividual changes, the model of strong MI was re-specified as a latent change model (Hertzog and Nesselroade 2003). Then, correlations between T1 performance level and latent changes across time were estimated, as well as the correlations among the latent changes of the four cognitive abilities. Table 3 shows the according values. For reasons of completeness, the correlations between the factors at T1 are also given. Here, all correlations were statistically significant, thus reflecting the typical picture of a positive manifold among cognitive abilities. Correlations were strongest between fluid intelligence and crystallized intelligence ($r = .74$) and between

[2] In a correlational metric, the difference is smaller, namely, $r = .34$ versus $r = .46$. Still, this implies that the amount of shared variance between memory and processing speed increased from 12 to 21%.

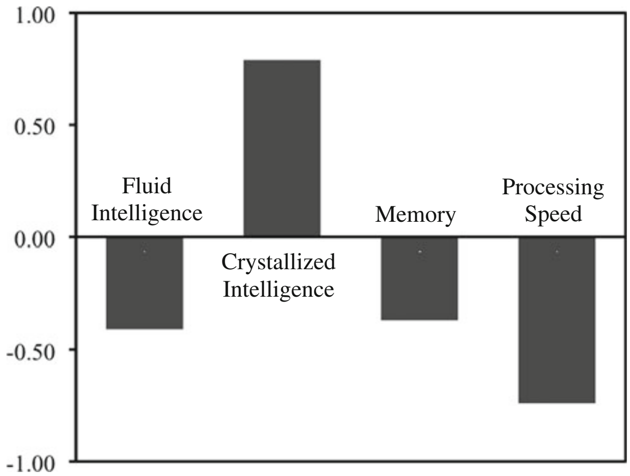

Fig. 1 Factor mean changes across 12 years, expressed as Cohen's *d* ($N = 346$)

fluid intelligence and processing speed ($r = .66$). In turn, the weakest correlation emerged between fluid intelligence and memory ($r = .21$). Hence, associations among the four cognitive factors were in the moderate to large range.

With respect to the relations among cognitive abilities at T1 and the changes in cognitive abilities, four correlations reached statistical significance. First, the correlations among fluid intelligence, crystallized intelligence, and memory with the change in crystallized intelligence were negative and in the small to moderate range. This implies that persons high in fluid intelligence, crystallized intelligence, and memory in 1994 showed a slightly lesser increase in crystallized intelligence across the 12 years. In turn, persons with a lower level in these three cognitive abilities at T1 exhibited a somewhat stronger increase in crystallized intelligence. Note that these negative correlations might also be indicative of a ceiling effect: Those who already ranked high at T1 had fewer possibilities to improve their performance. In addition, the correlation between memory in 1994 and change in memory was significant and of moderate negative size, implying that those high in memory at T1 declined more across time than those low in memory. Again, the measurement range may play a critical role here, albeit in the sense of an active floor effect: The decline of those scoring low in memory already in 1994 was hardly measurable.

Eventually, four correlations among the cognitive change factors were statistically significant. For changes in fluid intelligence and changes in crystallized intelligence, a correlation of $r = .72$ was estimated, implying that those who declined less in fluid intelligence improved more in crystallized intelligence—and vice versa. One might speculate that the strong correlation between changes in fluid intelligence and crystallized intelligence may be due to the fact that both factors share one manifest indicator, namely, picture completion. However, once picture completion is allowed to load on fluid intelligence only (or, alternatively, on crystallized intelligence only), the change correlation even increases ($r = .83$). Hence, there was a substantial amount of coupled change between these two cognitive abilities across a 12-year period during middle adulthood. The second strongest correlation emerged for changes in fluid intelligence and changes in processing speed ($r = .42$), indicating that those who showed a strong decline in fluid intelligence also had the tendency to decline more than average in processing speed. Finally, there was a moderate correlation between the changes in memory and processing speed ($r = .32$) and of the changes in memory and crystallized intelligence ($r = .23$), indicating that changes in memory and crystallized intelligence—albeit significantly correlated—still differ substantially.

Table 3 Factor and change factor correlations

	1.	2.	3.	4.	5.	6.	7.
1. Fluid intelligence at T1							
2. Crystallized intelligence at T1	.74						
3. Memory at T1	.21	.29					
4. Processing speed at T1	.66	42	.34				
5. Change in fluid intelligence	*−.09*	*−.04*	*.11*	*−.01*			
6. Change in crystallized int.	−.31	−.23	−.22	*−.07*	.73		
7. Change in memory	*.01*	*−.05*	−.36	*.07*	*.20*	.23	
8. Change in processing speed	*−.02*	*.01*	*.17*	*.19*	.42	*.07*	.32

Note: Correlations in italics are not statistically significant at $p < .05$. $N = 346$

Discussion

In this study, we set out to shed some light on a secret, namely, the question of whether cognition changes during middle adulthood. As we have argued, there are at least five different views of change within sample data, implying that cognition can change in different ways. As a prerequisite of examining the five types of change on the latent level, we first established strong MI for the four cognitive abilities fluid intelligence, crystallized intelligence, memory, and processing speed (cf. Meredith 1993). Note that such a finding deserves mention on its own, because it implies that the measurement properties of the ten cognitive tasks remained largely constant across time. Only the residual variances did change across time, implying that interindividual differences in manifest variables were not completely determined by the latent variables. Importantly, however, the fact that strong MI held allowed comparing factor variances, factor covariances, and factor means—the statistics describing the sample at T1 and T3 on the latent level.

Next, structural stability was investigated. The increasing covariance between memory and processing speed may represent a spurious result, because the overall test did not indicate any significant changes. Of course, statistical power is an issue here. Although covariances among factors are much less contaminated by measurement errors, they are estimated with less precision than covariances among manifest indicators. Hence, the standard errors of the former are larger than those of the latter. From this perspective, the results regarding the covariance between memory and processing speed are inconclusive. Still, we did not find hints for substantial differentiation or dedifferentiation processes in middle adulthood. Taking into account that we covered a 12-year period in our analysis, middle adulthood rather seems to be characterized by substantial structural stability—as opposed to old age, where at least in some studies dedifferentiation has been reported (cf. Ghisletta and de Ribaupierre 2005; de Frias et al. 2007).

Profound differential change only emerged for memory, although the three other factors did also not show perfect stability. As stability was modeled on the latent level, that is, unaffected by measurement error, correlations less than one do in some way mirror interindividual differences. Although concentrating on general intelligence rather than on specific cognitive abilities, the findings in our study resemble the findings from Hertzog and Schaie (1986). Memory performance not being stable may indicate that it is more strongly affected by environmental influences such as interindividually different demands at work or within the social environment (cf. Martin and Zimprich 2005).

Only for processing speed an increasing variance emerged, implying that development was heterogeneous with respect to this factor. Although covering a longer period of time, our findings are in line with the study from Martin and Zimprich (2005), which relied on 4-year data from ILSE. Change in processing speed therefore seems to be characterized by increasing interindividual differences, that is, individually differing change processes despite strong differential stability.

Results indicate that, in our study, statistically significant mean differences emerged for all cognitive variables, ranging from medium to strong effect sizes. Fluid intelligence, processing speed, and memory performance all showed significant decline, whereas in crystallized intelligence an increase emerged. This findings reflect the idea that crystallized intelligence still increases in adulthood while in more physiological cognitive functions such as fluid intelligence, memory, and, especially, processing speed decrease already sets in way earlier (cf. Cattell 1987).

A number of statistically significant change correlations emerged. The strongest correlation emerged between changes in fluid and crystallized intelligence. Note that this correlation is not due to the fact that fluid and crystallized intelligence shared a common manifest indicator. Individuals decreasing only slightly in fluid intelligence exhibited greater gain in crystallized intelligence. Again this finding stands in line with Cattell's (1987) theory regarding the development of fluid and crystallized intelligence, because fluid intelligence is considered to drive the acquisition of knowledge and contributing to the amount of knowledge an individual may gain across time. However, Cattell mainly concentrated on childhood and early adulthood as he postulated that the investment of fluid intelligence into crystallized extensively occurs during the schooling years. He did not provide a substantial framework for cognitive development in old age. Ackerman's (1996) Intelligence-as-process, personality, interests, and intelligence-as-knowledge theory relates the development of cognitive abilities to personality and interests. Here, it is suggested that, naturally, cognitive abilities determine the probability of success in a cognitive task, whereas personality and motivation determine the amount of effort an individual puts into attempting a special task. High cognitive abilities amplify motivation because the probability of success in a cognitive task increases. Success, in turn, functions as a reward and may lead to increased interest and motivation. Hence, a slight decrease in fluid intelligence affects the probability of success in knowledge acquisition less than a strong decrease and therefore does not constrain the motivation for knowledge acquisition as much as a strong decrease. A further possible explanation for this strong change correlation could be that both reflect relatively broad ability dimensions, drawing on the same cognitive resources.

Change in fluid intelligence also was correlated with processing speed in the sense that individuals showing greater decline in fluid intelligence also tended to decrease more in processing speed (Zimprich and Martin 2002). Assuming that both processes are more physiologically based and relatively independent of environmental factors, this correlation seems readily interpretable from a processing resources point of view (Salthouse 1996). Small, but statistically significant correlations emerged between memory and processing speed as well as memory and crystallized intelligence, respectively. Individuals showing a greater decline in memory also experienced a decline in processing speed, but a smaller increase in crystallized intelligence. Two things are noteworthy in this regard. First, the correlations among changes were weaker than correlations among factors at T1, albeit the longitudinal time span (12 years) is larger than the cross-sectional age range (5 years). One has to keep in mind, however, that the cross-sectional age range of 5 years has to be seen against a background of more than 40 years of development that has already taken place. In other words, the cross-sectional differences are also the result of 40 years of differential development, which may explain why the interindividual differences were more strongly correlated than interindividual differences in intraindividual change.

Second, compared to results from studies with older adults, change correlations also appear to be weaker in middle-aged adults (cf. Christensen et al. 2004; Hultsch et al. 1998; Zimprich 2002; Zimprich and Martin 2009). Note that, as Hofer and Sliwinksi (2001) have shown—all other things being equal—in the long run the cross-sectional correlation between two variables will approach the correlation between the (linear) change in the two variables (cf. Zimprich 2002). From this one would expect that cross-sectional correlations between cognitive abilities would decrease down to the change correlations, i.e., that they differentiate slightly. The exception would be fluid and crystallized intelligence, where the change correlation was comparatively strong. However, in comparing cross-sectional and change correlations, one should consider that the signal-to-noise ratio is better in cross-sectional data than in change data. In other words, change correlations are expected to fluctuate much more than cross-sectional correlations. In addition, during development into old age, change processes may become more strongly intertwined because of more pronounced changes in cognitive abilities. Thus, change correlations among cognitive abilities could be stronger in old age than in middle-aged adults.

Taken together, what do these results say about the secret of cognitive change during middle adulthood? Mean performance changes are very similar to those changes in older adults, except maybe that crystallized intelligence increased strongly in middle-aged adults while the decrease in memory performance corresponded to a moderate effect size only. However, the overall pattern of mean changes nicely maps onto those of cognitive performance changes in later years of life. A different picture emerged from the other four types of change. Interindividual differences in cognitive performance across 12 years appeared to be remarkably stable. This is to say that from a between-persons perspective focus on interindividual differences in change, stability seems to outweigh change. Notwithstanding, relatively seen it was memory performance and processing speed that appeared to be especially vulnerable to changes during middle adulthood, as was indicated by the covariance between both tending to increase, the low differential stability of memory and the significant variance change in processing speed. Finally, the strongly correlated change between fluid and crystallized intelligence has, absent of structural change, differential change, and change in divergence in these two abilities, also a stabilizing effect, because it perpetuates interindividual differences.

References

Ackerman PL (1996) A theory of adult intellectual development: process, personality, interests, and knowledge. Intelligence 22:227–257

Allemand M, Zimprich D, Hertzog C (2007) Cross-sectional age differences and longitudinal age changes of personality in middle adulthood and old age. J Pers 75:323–358

Anstey KJ, Hofer SM, Luszcz MA (2003) Cross-sectional and longitudinal patterns of dedifferentiation in late-life cognitive and sensory function: the effects of age, ability, attrition, and occasion of measurement. J Exp Psychol Gen 132:470–487

Babcock RL, Laguna KD, Roesch SC (1997) A comparison of the factor structure of processing speed for younger and older adults: testing the assumption of measurement equivalence across age groups. Psychol Aging 12:268–276

Baltes PB, Cornelius SW, Spiro A, Nesselroade JR, Willis SL (1980) Integration versus differentiation in fluid/crystallized intelligence in old age. Dev Psychol 16:625–635

Bickley PG, Keith TZ, Wolfle LM (1995) The three-stratum theory of cognitive abilities: test of the structure of intelligence across the life span. Intelligence 20:309–328

Bollen KA (1989) Structural equations with latent variables. Wiley, New York

Box GEP, Cox DR (1964) An analysis of transformations (with discussions). J R Stat Soc 26:211–252

Browne MW, Cudeck R (1993) Alternative ways of model fit. In: Bollen KA, Long JS (eds) Testing structural equation models. Sage, Newbury Park, pp 136–162

Cattell RB (1987) Intelligence: its structure, growth and action. North Holland, Amsterdam

Christensen H, Mackinnon A, Jorm AF, Korten A, Jacomb P, Hofer SM, Henderson S (2004) The Canberra longitudinal study: design, aims, methodology, outcomes, and recent empirical investigations. Aging Neuropsychol Cogn 11:169–195

Cohen J (1987) Statistical power analysis for the behavioral sciences, Rev. edn. Erlbaum, Hillsdale

Cunningham WR, Birren JE (1980) Age changes in the factor structure of intellectual abilities in adulthood and old age. Educ Psychol Meas 40:271–290

Cunningham WR, Clayton V, Overton W (1975) Fluid and crystallized intelligence in young adulthood and old age. J Gerontol 30:53–55

de Frias CM, Lövdén M, Lindenberger U, Nilsson L-G (2007) Revisiting the dedifferentiation hypothesis with longitudinal multi-cohort data. Intelligence 35:381–392

Finkel D, Pedersen NL, Plomin R, McClearn GE (1998) Longitudinal and cross-sectional twin data on cognitive abilities in adulthood: the Swedish adoption/twin study of aging. Dev Psychol 34:1400–1413

Finkel D, Reynolds CA, McArdle JJ, Gatz M, Pederson NL (2003) Latent growth curve analyses of accelerating decline in cognitive abilities in late adulthood. Dev Psychol 39:535–550

Ghisletta P, de Ribaupierre A (2005) A dynamic investigation of cognitive dedifferentiation with control for retest: evidence from the Swiss interdisciplinary longitudinal study on the oldest old. Psychol Aging 20:671–682

Ghisletta P, Lindenberger U (2003) Age-based structural dynamics between perceptual speed and knowledge in the Berlin Aging

Study: direct evidence for ability dedifferentiation in old age. Psychol Aging 18:696–713
Hertzog C, Bleckley MK (2001) Age differences in the structure of intelligence: influences of information processing speed. Intelligence 29:191–217
Hertzog C, Nesselroade JR (2003) Assessing psychological change in adulthood: an overview of methodological issues. Psychol Aging 18:639–657
Hertzog C, Schaie KW (1986) Stability and change in adult intelligence: 1. Analysis of longitudinal covariance structures. Psychol Aging 1:159–171
Hertzog C, Schaie KW (1988) Stability and change in adult intelligence: 2. Simultaneous analysis of longitudinal means and covariance structures. Psychol Aging 3:122–130
Hess TM (2005) Memory and aging in context. Psychol Bull 131:383–406
Hofer SM, Sliwinksi MJ (2001) Understanding ageing: an evaluation of research designs for assessing the interdependence of ageing-related changes. Gerontology 47:341–352
Horn W (1983) Leistungsprüfsystem L-P-S (2., erw. Aufl.) [Battery of performance examination tests]. Hogrefe, Göttingen
Horn JL (1985) Remodeling old models of intelligence. In: Wolman BB (ed) Handbook of intelligence. Wiley, New York, pp 267–300
Horn JL, McArdle JJ (1992) A practical and theoretical guide to measurement invariance in aging research. Exp Aging Res 18:117–144
Hultsch DF, Hertzog C, Dixon RA, Small BJ (1998) Memory change in the aged. Cambridge University Press, Cambridge
Juan-Espinosa M, García LF, Colom R, Abad FJ (2000) Testing the age differentiation hypothesis through Wechsler's scales. Pers Individ Dif 29:1069–1075
Juan-Espinosa M, García LF, Escorial S, Rebollo I, Colom R, Abad FJ (2002) Age dedifferentiation hypothesis: evidence from the WAIS-III. Intelligence 30:395–408
Larsen L, Hartmann P, Nyborg H (2008) The stability of general intelligence from early adulthood to middle-age. Intelligence 36:29–34
MacCallum R, Browne M, Sugawara HM (1996) Power analysis and determination of sample size for covariance structure modeling. Psychol Methods 2:130–149
Martin M, Zimprich D (2005) Cognitive development in midlife. In: Martin M, Willis SL (eds) Middle adulthood: a lifespan perspective. Sage, Thousand Oaks, pp 179–206
Martin M, Grünendahl M, Schmitt M (2000) Persönlichkeit, kognitive Leistungsfähigkeit und Gesundheit in Ost und West: Ergebnisse der Interdisziplinären Längsschnittstudie des Erwachsenenalters (ILSE). Zeitschrift für Gerontologie und Geriatrie 33:111–123
McArdle JJ, Prescott CA (1992) Age-based construct validation using structural equation modeling. Exp Aging Res 18:87–115
Meredith W (1993) Measurement invariance, factor analysis, and factorial invariance. Psychometrika 58:525–543
Meredith W, Horn JL (2001) The role of factorial invariance in modeling growth and change. In: Collins LM, Sayer AG (eds) New methods for the analysis of change. American Psychological Association, Washington, pp 203–240
Neale MC, Boker SM, Xie G, Maes HH (2003) Mx: statistical modeling, 6th edn. Department of Psychiatry, Richmond
Oswald WD, Fleischmann UM (1995) Nürnberger-Alters-Inventar (NAI) [Nuremberg inventory of old age]. Hogrefe, Göttingen
Oswald WD, Roth E (1987) Der Zahlen-Verbindungs-Test (ZVT) [The number connecting test]. Hogrefe, Göttingen
Park DC, Lautenschlager G, Hedden T, Davidson NS, Smith AD, Smith PK (2002) Models of visuospatial and verbal memory across the adult lifespan. Psychol Aging 17:299–320
Preece PF (1982) The fan-spread hypothesis and the adjustment for initial differences between groups in uncontrolled studies. Educ Psychol Meas 42:759–762
Salthouse TA (1996) The processing-speed theory of adult age differences in cognition. Psychol Rev 103:403–428
Schaie KW (1974) Translations in gerontology—from lab to life Intellectual functioning. Am Psychol 29:802–807
Schaie KW (1994) The course of adult intellectual development. Am Psychol 49:304–313
Schaie KW (1996) Intellectual development in adulthood—the Seattle Longitudinal Study. Cambridge University Press, Cambridge
Schmidt DF, Botwinick J (1989) A factorial analysis of the age dedifferentiation hypothesis. In: Schaie KW, Bengston VL (eds) The course of later life: research and reflections. Springer, New York, pp 87–92
Sims RC, Allaire JC, Gamaldo AA, Edwards CL, Whitfield KL (2009) An examination of dedifferentiation in cognition among African-American older adults. J Cross Cult Gerontol 24:193–208
Soederberg Miller LM, Lachman ME (2000) Cognitive performance and the role of control beliefs in midlife. Aging Neuropsychol Cogn 7:69–85
Tewes U (1991) Hamburg-Wechsler-Intelligenztest für Erwachsene, Revision 1991 (HAWIE-R) (2.Auflage) [Wechsler Adult Intelligence Scale—revised (WAIS-R)]. Huber, Bern
Tomer A, Cunningham WR (1993) The structure of cognitive speed measures in old and young adults. Multivariate Behav Res 28:1–24
Tucker-Drob EM, Salthouse T (2008) Adult age trends in the relations among cognitive abilities. Psychol Aging 23:453–460
Zelinsky EM, Lewis KL (2003) Adult age differences in multiple cognitive functions: differentiation, dedifferentiation, or process-specific change? Psychol Aging 18:727–745
Zimprich D (2002) Kognitive Entwicklung im Alter - Die Bedeutung der Informationsverarbeitungsgeschwindigkeit und sensorischer Funktionen für den kognitiven Alterungsprozess [Cognitive development in old age—on the significance of processing speed and sensory functioning for cognitive aging]. Dr. Kovac, Hamburg
Zimprich D, Martin M (2002) Can longitudinal changes in processing speed explain longitudinal changes in fluid intelligence? Psychol Aging 17:690–695
Zimprich D, Martin M (2009) A multilevel factor analysis perspective on intellectual development in old age. In: Bosworth HB, Hertzog C (eds) Aging and cognition: research methodologies and empirical advances. APA, Washington, pp 53–76
Zimprich D, Allemand M, Hornung R (2006) Measurement invariance of the abridged sense of coherence scale in adolescents. Eur J Psychol Assess 22:280–287